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An Agent's Activities Are Controlled by His Priorities

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Abstract. Activity scheduling mechanism plays a critical role in the correct behaviour of BDI agents. For example, a robotic agent to serve at home should carry out the right activities at the right times. However the scheduling of deliberation about new beliefs and the scheduling of intention execution have not been carefully studied in most BDI systems. Usually if there is any differentiation of urgency among different tasks, a constant utility/priority value is used by a task selection function. We argue that priorities should be allowed to change with time and a linear function of time may not be the best for all tasks. In this paper, we propose to enrich the BDI framework with an extension which consists of 2 processing components, a PCF (Priority Changing Function) Selector and a Priority Controller. With this extension priorities of desires/intentions may have different initial values and may be changed with time according to the chosen PCFs. We propose a method of constructing PCFs which model the change of priorities in human behaviors when dealing with several things at the same time. We also propose a method to realize the change of the priorities of existing desires/intentions due to the generation of new beliefs/desires/intentions if necessary. We show by simulation experiments that Ramp function and especially the Sigmoid function can control the activities of an agent better than constant priorities with respect to getting tasks of various importance and urgency done with smaller Mean Earliness and smaller Mean Tardiness.

1 Introduction

Bellman defines AI in [1] as the automation of activities that we associate with human thinking, activities such as decision making, problem solving, and learning. One such activity is to decide when is the appropriate time to think about a certain matter or to do something. For an intelligent agent, this means it should know when to deliberate and when to act in addition to being able to deliberate on how to achieve a goal and how to carry out a plan. There has been significant amount of work on solving the “How” problem but not the “When” problem. For example, the PRS (procedural reasoning system) obtains the ability of reasoning in complex ways about dynamic processes while keeping appropriate responsiveness and control [5]. AgentSpeak(L) [8] and LORA (logic of rational agents) [9] are two sets of operational semantics

defined for BDI agents. The decision is made through logic reasoning. All these works are solutions to the “How” question.

The “When” question, that is, the scheduling of deliberation about new beliefs and the scheduling of intention execution are usually omitted in these BDI systems. For example, in AgentSpeak(L) [8], the selection function S_I selects an intention to execute from the intention set I . The detailed selection criteria are not specified. We believe the scheduling of intention is crucial in an agent’s ability to cope with the changing world. Some scheduling mechanisms appear in subsequent researches. In AgentSpeak(XL) [2], an extension version of AgentSpeak(L), a task scheduler is incorporated into the interpreter to decide how to select intentions. The set of intentions in the AgentSpeak(L) is converted into a corresponding TÆMS task structure. The ‘enables’ and ‘hinders’ relationships among the plans indicate which plan may be executed first. Another method is shown in the JAM agent architecture [4]. The intention selection is based on the utility value of the plan set by the user. The intention with higher utility will be executed first.

We consider the problem of deliberation scheduling and intention scheduling in an agent who will behave like an “average human”. We associate a single priority value with each desire or intention to facilitate the scheduling of deliberations and intention executions. For humans, their priorities change with time. The priorities may be affected by how close it is to the deadline of a task, or how appropriate it is to do a certain task at a certain time from human point of view. The deadlines of tasks may also change, either forward or backward. Therefore to represent the priority of a goal or an intention of an agent realistically, a function of time should be used instead of a constant value. Representing the priority of a desire/intention by a function of time instead of a constant also has another advantage. If the priority is a constant and there are other desires/intentions with higher priorities continuously being generated, this lower priority desire/intention will never have a chance of being considered.

Currently, the control of the priority changing with time has not been adequately researched even though some work has been done in the artificial life community. In [6], a priority control mechanism for behavioral animation is proposed. The priority is set at minimal value immediately after the agent displays certain behaviour like drinking. Then this priority increases with time. The increased priority will induce the agent to drink again. However, expecting the priorities of all desires and intentions to change in the same manner is not realistic. Different desires and intentions should be allowed to change their priorities in various suitable ways.

A parallel BDI agent framework was proposed in [10] to achieve better reactivity and rationality in intelligent agents. This framework equips a BDI agent with the natural abilities of doing several things at the same time and the ability of prioritizing the deliberations and intention executions according to the urgency of the tasks. The level of priority is used in the scheduling of the desires/intentions in the agent. However this mechanism has the problem that with priorities set at constant levels, some desire or intention may be starved indefinitely by desires or intentions with higher levels of priorities.

In this paper, we proposed a priority control extension to the parallel BDI agent framework [10] in order to support the capabilities of representing the changing importance of different desires and intentions. This is an extension of the paper in [11]

where only independent intentions are considered. Pre-defined *Priority Changing Functions (PCFs)* are associated with the desires and intentions. A Priority Controller will compute the priority value of the desires and intentions to help the scheduling decisions to be made at various time moments. We propose a method of constructing PCFs which model the change of priorities in human behaviors when dealing with several things at the same time. The remainder of this paper is structured as follows. In Section 2, we present the BDI agent framework with the proposed extension of priority control. In Section 3, we discuss the mechanisms of priority controls proposed. The priority control functions are evaluated in Section 4. At the end of the paper, we summarize the contribution of the paper and future work.

2 BDI Agent Framework with the Priority Control Extension

The parallel BDI agent framework consists of three main components running in parallel: the belief manager, the intention generator and the intention executor. These three components represent the three steps in the deliberation process of an agent: *detect*, *think* and *act* respectively. The three components will retrieve and update data in the three data structures: *beliefs*, *desires*, and *intentions*. The *beliefs* contain the agent's view of its environment and of itself. The *desires* will maintain the goals of the agent. The *intentions* store the plans to be executed to achieve the agent's goals. Higher priority beliefs, desires and intentions preempt the processing of lower priority ones in the parallel running components.

Fig. 1. Priority control extension to the parallel BDI framework (only parts of the original framework [10] that interact with the extension are shown).

To represent the dynamic change of priorities of a desire or intention, each desire or intention will be associated with a Priority Changing Function (PCF) which defines how the priority should change with time. The priority control extension to the agent architecture is shown in Figure 1. Two processing components are introduced into the

BDI agent, a PCF (Priority Changing Function) Selector and a Priority Controller. When a desire/intention is generated, the intention generator will call on the PCF Selector which will, based on some context-rules, (i) select a suitable PCF for the new desire/intention from the PCF Library and (ii) decide on the values of the parameters if any for the PCF. The signature of the function of the PCF Selector is as follows:

$PCF_Selector : desires \times PCFs \rightarrow PCFs$ and $PCF_Selector : intentions \times PCFs \rightarrow PCFs$ where *desires* and *intentions* are the set of desires and the set of intentions of the agent respectively and *PCFs* is the set of priority changing functions in the PCF library. More discussions on the PCF Selector are given in Section 3.3.

The Priority Controller will be responsible for updating the priorities of the desires/intentions according to their PCFs as time passes. In order to have the priorities of desires and intentions assessed accurately but not computed unnecessarily, the Priority Controller will update the priorities of desires/intentions each time the BDI agent is to select a desire/intention to execute by

$$Priority = f(t) \quad (1)$$

where, $f(t)$ is the PCF and t is the current time.

This extension allows a BDI agent to select suitable pre-defined PCFs for the desires/intentions and compute the priority values of desires/intentions at various points in time. Then the deliberation of the desires and the execution of the intentions can be scheduled by the Intention Generator or the Intention Executor based on their importance or urgency, represented by their priority values at the time. This enriches the BDI agent with the ability of realizing the scheduling of the desires/intentions in a more realistic way.

3 Priority Control

With the architectural support as described in the previous section, we present in this section the mechanism of priority control so that what an agent deliberates and acts on are decided by his priorities, just like the humans. The basic control of priorities comes from the Priority Changing Function (PCF) which defines how the priority of a desire or an intention should change with time. The PCF is defined by

$$f(t) = \text{Maximum priority} * I(t) \quad (2)$$

where *Maximum priority* is the highest value which a desire or an intention may have; $I(t)$ is the function of influence factor with a range $[0, 1]$. *Maximum priority* is an intrinsic constant value of a desire or an intention where $I(t)$ controls the changes in priority with time. This PCF with a suitable $I(t)$ will be applied in the parallel BDI agent to provide some human-like behaviour. $I(t)$ can be different for different desires and intentions.

Very often, human interests in a certain goal or intention go through a few phases. According to Maslow's theory of hierarchy of needs [7], a need will increase along with other needs. During the process a need is being satisfied, it will lose its dominance. So one phase is the period when the interests are getting stronger and stronger

and we call it the reminding phase. Another phase is the period when the interests or appropriateness will become less and less and occasionally the goal or intention may even be forgotten so this is called the forgetting phase. There are also situations where someone has an unchanging interest to do something and this is called the unchanging phase. We will first describe how $I(t)$ models the various phases of priority changing and then show how the various phases work together. Then we will present how the effect of a new belief/desire/intention on some existing desire/intention is modeled.

3.1 The Reminding Phase of a PCF

This is the phase where an agent has increasing inclination to deliberate on how to achieve a goal or to execute an intention plan. The priority of the goal or intention should increase gradually until it reaches its maximum value. We call this phase the ‘reminding’ phase. The manner by which the priority of a desire or an intention increases may be different from that of the others. We propose two different functions to model the way a priority may increase, the ramp and Sigmoid functions.

For the two functions, the value $I(t)$ at $t = 0$ is y_0 . The value of y_0 when multiplied by the maximum priority as shown in Equation (2) will return $f(t)$ the initial priority of a desire or intention. And at $t = t_m$, the value of $I(t)$ should be 1 or very close to 1. t_m is the time when $f(t)$ is to reach its maximum priority value. The ramp function is a model where the priority increases at a constant rate. It is realized by:

$$I(t) = y_0 + \frac{1 - y_0}{t_m} * t \quad (3)$$

To simulate the reminding phase using the Sigmoid function, we extract part of the Sigmoid curve between $[-\alpha, \alpha]$ in x-axis, $0 < \alpha < 0.5$. The original Sigmoid curve is shifted to right by $\ln\left(\frac{1}{\alpha} - 1\right)$ in x-axis. Then the curve between $[\alpha, 1 - \alpha]$ in y-axis will be resized to $[0, t_m]$ in x-axis and $[y_0, 1]$ in y-axis. We get the equation:

$$I(t) = \left[\left[1 + \exp\left(\left(1 - \frac{2t}{t_m}\right) * \ln\left(\frac{1}{\alpha} - 1\right)\right) \right]^{-1} - \alpha \right] * \frac{(1 - y_0)}{(1 - 2\alpha)} + y_0 \quad (4)$$

Sigmoid functions with different α , t_m and y_0 exhibit different shapes of the function. With a smaller α , the function simulates a slower rise at the beginning followed by a steeper increase of priority and then a slow rise near time t_m . By controlling the value of α , we can control the way the priority increases over time within the pattern of Sigmoid function.

The Sigmoid function has the property that the gradient of $I(t)$ gradually decreases to zero when t approaches t_m . This simulates the increase in the agent’s interest in a goal or an intention gradually stops as the interest reaches its maximum. For (4), (i) $I(t)$ is increasing for $t \leq t_m$; (ii) the rate of increase first increases for $0 \leq t \leq t_m - \sigma$ ($I''(t) \geq 0$) and then decreases for $t_m - \sigma \leq t \leq t_m$ ($I''(t) < 0$); (iii) the increase in function

value and the rate of increase at t_m are 0, which means that the trend to increase the priority has stopped.

Table 1. Results with different α for the Sigmoid function.

Inter-arrival mean = 25												
α	0.1 – 0.3			0.4 – 0.6			0.7 – 0.8			0.9		
	Pass (%)	Mean Earliness	Mean Tardiness	Pass (%)	Mean Earliness	Mean Tardiness	Pass (%)	Mean Earliness	Mean Tardiness	Pass (%)	Mean Earliness	Mean Tardiness
.100	25.6	-46.10	332.39	60.8	-43.57	34.90	83.4	-49.28	9.97	88.1	-49.84	4.56
.0500	28.2	-42.53	309.74	62.4	-42.04	33.35	81.7	-47.33	10.67	88.5	-51.30	4.99
.0250	35.7	-46.69	291.15	65.3	-45.85	37.64	81.6	-48.47	9.55	89.0	-50.77	3.16
.0218	31.7	-39.45	269.52	63.1	-44.27	26.94	82.8	-41.53	10.53	94.5	-46.96	1.13
.0187	29.6	-41.67	263.76	60.3	-40.34	42.54	78.7	-44.92	15.62	83.5	-48.49	5.75
.0125	33.4	-42.79	343.15	53.8	-38.57	44.40	72.0	-41.21	10.48	82.1	-45.00	4.36
0	21.4	-39.20	272.14	31.6	-69.08	46.57	42.8	-54.74	12.92	49.5	-59.01	3.61

To demonstrate the way to set an optimal value for α , a simulation experiment is done in which 100 events arrives according to an exponential distribution of mean = 25 time units. $t_m = T_C - T_E$, where T_C is the time by which the task should be completed, T_E is the execution time a certain task takes.. The T_E of each event is assigned a random execution time between 1 and 49 with mean = 25 time units. The T_C for each event is between $1.25T_E$ to $8T_E$ which means events are known in advance of their deadline by different amount of time, some are known much earlier than others. The events are divided into four groups according to their maximum priorities MP: 0.1-0.3, 0.4-0.6, 0.7-0.8 and 0.9. y_0 is 0.05MP. The experiment results are shown in Table 1. In the Table, Pass (%) is the percentage of events meeting deadlines, Mean Earliness is the Average time left for which jobs are finished before the deadline, and Mean Tardiness is the Average time by which jobs are finished after the deadline. Binary search is done for the value of α to achieve high Pass rate, small Mean Tardiness, especially for high priority events, and small Mean Earliness. As we see, with $\alpha = 0.0218$, the agent has the best performance.

3.2 The Forgetting Phase and the Unchanging Phase of a PCF

The forgetting phase is the phase where an agent's interest in a goal or an intention plan is fading, or the appropriateness of doing a certain task is diminishing with time. For example, cleaning windows is better done in day time and it is getting late. In this case, the priority of the goal or the intention should be decreased gradually. So if the agent has other intentions with higher priorities like serving some guests, he should delay cleaning windows. If the priority decreases to a value below a threshold, which corresponds to that it is too late to clean windows, the intention will be removed (forgotten). The first significant study on memory was performed by Hermann Ebbinghaus and published in 1885 as *On Memory*. Ebbinghaus was the first to describe the shape of the forgetting curve [3]. This curve is the biological base on which we simulate the process of intention retention. The forgetting curve is described as:

$$R = e^{-t/S} \quad (5)$$

where R is the retention, which means the ability to retain things in memory; t is the elapsed time; S is the strength of memory, which means the duration of things in memory. The forgetting curves with different S exhibit different rates of decay of priority. The smaller S corresponds to a shorter retention interval. When S is a very big value, there will be little forgetting and priority will decrease very slowly.

The unchanging phase is the phase where an agent's interest in a goal or an intention plan is at a constant level. The priority of the goal or the intention is specified by a constant.

3.3 The Complete PCF

The complete PCF, or more specifically, the complete $I(t)$ is formed by either any one of the single phased functions described earlier, or it is a concatenation of two or more single phased functions. For example, we can compose an $I(t)$ by combining the functions of the reminding phase and the forgetting phase together. The result is a reminding-forgetting function:

$$I(t) = \begin{cases} y_0 + \frac{1-y_0}{t_m} * t & \text{if } t \leq t_m \\ \exp\left(-\frac{t-t_m}{S}\right) & \text{otherwise} \end{cases} \quad (6)$$

An example of the situation modeled by this $I(t)$ is that an agent intends to clean windows starting latest by t_m if he finds the time. After t_m it becomes less desirable to clean windows so the priority goes into the forgetting phase. We can in fact append a constant priority phase with value 0 for this intention for the evening and night time and another reminding phase for next morning. The same can be done to simulate Maslow's theory of hierarchy of needs [7], where a need will increase and after it is satisfied, it will lose its dominance. All these information can be considered by the PCF Selector in order to choose a suitable PCF. In the simplest case, a constant priority function can be chosen for a desire/intention that has no deadline and the sigmoid/ramp function for one that has. The default will be the sigmoid function. As shown by the experiments presented later in the paper, the sigmoid function helps to have tasks finished with smallest Mean Tardiness and Mean Earliness in general. When more information about a desire/intention is available, the PCF Selector will be able to choose the PCF that best suits the desire/intention.

3.4 Priority Change Caused by Other Beliefs/Desires/Intentions

It is noticed that the $I(t)$ function as described earlier changes the priority of a desire or an intention in the absence of the effect of new beliefs, desires and intentions. However, a new belief/desire/intention may make an existing desire/intention more

urgent or less urgent, therefore the priority of the affected desire or intention needs to be increased or decreased. For example, suppose the human master asked his robotic agent to wash his car while the agent is doing cleaning in the house and the robotic agent also has a few other things to do. The agent has the intention to wash the car but the priority is not as high as his other intentions. After a little while the master reminds the agent about washing his car. At this point the priority for washing the car should be increased. So the new belief that the car needs to be washed sooner should have the effect of increasing the priority of the intention of washing the car. Another scenario that will change the priority of an existing intention: the robotic agent has the intention to tidy up a room but his master tells him to iron a shirt in the next 10 minutes. The robotic agent generates the intention to iron the shirt and has to lower the priority of tidying up the room. In situations like these examples, the priority of an existing desire/intention at t and beyond is affected. t is the time when a new belief, a new desire or a new intention is generated and it is the moment when the priority of an existing desire/intention should be changed if it is affected.

To model the effect on the $I(t)$ of the existing desire/intention, one simple way to do it is to change the T_C value and therefore the t_m value in $I(t)$ is changed. This results in an increase or decrease of the $I(t)$ value at t which brings the increase or decrease of the priority of the affected desire/intention.

4 Evaluation of PCFs

To examine how the PCFs perform in controlling the scheduling of activities, another set of experiments is done to compare the performance of agents with priorities changed by the Ramp, Sigmoid reminding functions, and with static priorities. The way the experiments are set up is the same as in Table 1. Three different event inter-arrival means are used in 3 groups of experiments. For each group of experiments, multiple runs are conducted to obtain the average of Pass rate, Mean Earliness and Mean Tardiness. The results are shown in Table 2.

The first group of experiments presents the situation where inter-arrival mean which is 20 is smaller than the average processing time of events T_E which is 25 time units. In such a situation, priority control with the static values produces very high Pass rate and small tardiness but also large earliness for the highest priority events. At the same time, the lowest priority events suffer from very low Pass rate and huge tardiness. The Ramp function has the lowest Pass rate for all events and the Sigmoid function returns better Tardiness and better earliness for almost all events but the Pass rate for all events except the lowest priority ones is lower than the static priority.

In the second group of experiments, the event inter-arrival mean is equal to the average processing time of events. Ramp function again produces the worst Pass rate but its tardiness and earliness are better than the static function for all events with the only exception in the tardiness of the highest priority events. Sigmoid function has better Pass rate than the static function for the lowest priority events and comparable Pass rate for other events. Its tardiness and earliness are all better than the static function for all events.

When the event inter-arrival mean is larger than the average processing time of events in the third group of experiments, Ramp function returns comparable Pass rate and better tardiness and earliness for all events than the static function except the slight increase in tardiness for the highest priority events. Sigmoid function generates better Pass rate for the lowest priority events and comparable Pass rate for other events. It also achieves smaller tardiness and earliness for almost all events.

The general conclusion from the experimental results is that static priority guarantees that high priority events(priority = 0.9) have high Pass rate and small Mean Tardiness at the expense of the lower priority ones(priority = 0.1 to 0.3). As the priority of events decreases, the Pass rate decreases and Mean Tardiness increases. This confirms that the lower priority events tend to be starved of processing time under static priority. The Ramp PCF and especially the Sigmoid PCF are able to reduce the tardiness and increase the Pass rate for low priority events, reduce the tardiness and earliness of most events with a small increase of tardiness for high priority events. This means more events are handled not too early and not too late and we can conclude that using these PCFs produces more desirable behaviour in BDI agents.

Table 2. Results of agents with different PCFs.

PCF	0.1 – 0.3			0.4 – 0.6			0.7 – 0.8			0.9		
	Pass (%)	Mean Earliness	Mean Tardiness	Pass (%)	Mean Earliness	Mean Tardiness	Pass (%)	Mean Earliness	Mean Tardiness	Pass (%)	Mean Earliness	Mean Tardiness
Inter-arrival mean = 20												
Static	6.8	-57.342	1215.936	45.0	-80.769	257.975	84.5	-81.017	42.552	96.9	-86.467	5.009
Ramp	8.9	-31.288	494.061	24.7	-47.459	165.464	42.6	-46.182	78.571	58.1	-50.134	53.733
Sigmoid	14.0	-32.282	631.128	33.5	-31.702	93.431	56.8	-32.323	18.767	73.2	-34.469	7.467
Inter-arrival mean = 25												
Static	21.7	-66.847	637.102	64.2	-76.525	112.0	89.9	-89.622	25.009	98.1	-89.606	2.483
Ramp	23.2	-48.96	213.96	51.3	-52.48	60.75	71.2	-50.95	33.48	80.1	-59.16	14.71
Sigmoid	31.7	-39.45	269.52	63.1	-44.27	26.94	82.8	-41.53	10.53	94.5	-46.96	1.13
Inter-arrival mean = 30												
Static	48.8	-81.879	202.074	77.0	-82.931	58.982	92.6	-88.243	13.898	99.6	-90.023	0.330
Ramp	49.5	-61.059	93.621	79.4	-60.304	24.878	90.5	-63.874	8.912	95.9	-68.647	2.710
Sigmoid	55.4	-55.370	144.777	80.0	-52.034	18.946	92.7	-59.889	4.897	94.3	-60.029	1.949

5 Conclusion and Future Work

In this paper, we propose to enrich the BDI agent framework with the priority control extension consisting of 2 processing components, a PCF (Priority Changing Function) Selector and a Priority Controller. This provides the support at the architecture level for the control of priorities of desires and intentions that may have different initial values and will change with time according to the chosen PCF. This enables the automation of the scheduling of the agent's activities in a more human-like manner and removes the need for the scheduler to reason about deadlines when selecting activities. A method to compose priority changing functions from single phases of priority change is proposed. This is a flexible way to model the change of priorities in human

activities. Different priority functions will introduce different behaviour in an agent's decision on when an activity should be done. We also propose a method to realize the change of the priorities of existing desires/intentions due to the generation of new beliefs/desires/intentions if necessary. Experimental results show that using these PCFs produces more desirable behaviour in BDI agents.

One shortcoming in this method at the moment is that it can only consider a one to many relationship, that is, the effect of one new belief/desire/intention on the existing desires/intentions. When intention A makes both intention B and intention C more urgent, changing the value of t_m in the PCFs of B and C separately and independently may not be appropriate. Another unresolved yet important issue is how to decide the maximum priority of a task. The parameter, if not set properly, may result in the agent switching between tasks in an unnatural way. However, we believe one way is to let the agent learn from its experience like humans learn time management. The agent may use a neural network and first go through supervised learning to obtain parameter values for a set of 'anchor' tasks. Subsequently, the agent may infer values for other tasks which are similar to some anchor tasks. These issues are the subjects of our future work.

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